Likelihood Calibration of a Soil Moisture Model with Radar Backscatter to Account for Speckle

Nearing, G.S. and Moran, M.S.

University of Arizona and USDA-ARS Southwest Watershed Research Center

Introduction

Radar backscatter can contain information about water in soils, however tracking soil moisture patters using satellite based instruments is difficult due to infrequent imaging and the strong effects of speckle which require spatial aggregation in order to extract soil moisture information. By calibrating a land surface model (LSM) to backscatter image data it may be possible to temporally track soil moisture behavior between overpasses (**figure 1 top**), however the amount of aggregation necessary to account for speckle reduces the spatial information density beyond what is acceptable for some applications when extracting information from a single image. Since the LSM provides correlation between soil moisture values at different times, via knowledge of atmospheric and other forcing conditions, it may be possible to exploit this correlation (**figure 1 bottom**) to reduce the spatial aggregation necessary for extracting soil moisture information from a backscatter image series.

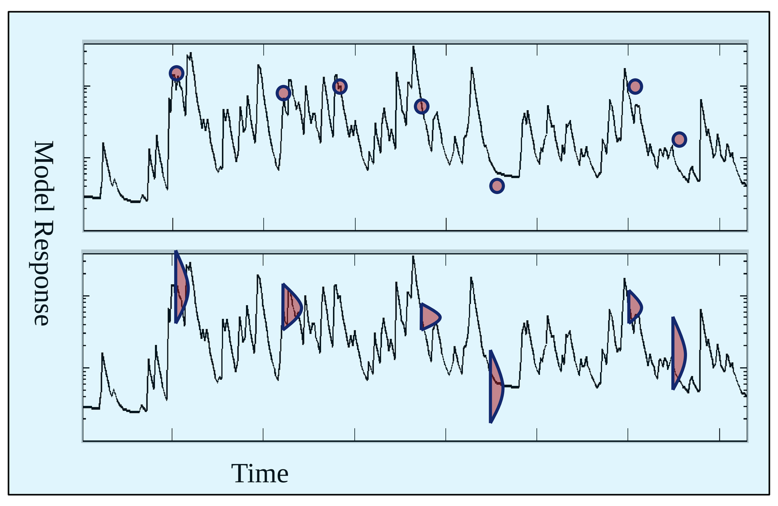

Figure 1:
Top - Continuous modeled SM (black line) fit to observed data (red dots)

Bottom *- Modeled response follows most likely path through uncertain data.*

A likelihood measure is developed for estimating the information carrying parameter in a speckle model which can simultaneously consider samples from both a homogenous area in a single backscatter image and in many images of a homogenous area over time. Although the information carrying parameter changes with changes in soil moisture - and thus between images - the LSM will track these changes using knowledge of precipitation and abstractions. Since the information carrying parameter in a backscatter image can be directly related to soil moisture a LSM which provides a time series of theoretical backscatter behavior related to soil moisture estimations (**figure 2**) can by calibrated to raw image data by maximizing this likelihood function.

The Committee on Watershed Management has outlined a set of target accuracy and precision requirements for soil moisture information retrieval (**table 1**).

Mapping Parameter	**Requirement**
Spatial Resolution	*10 to 100 m*
Vertical resolution Root zone, 15 cm to >1 m	*15 cm to > 1 m; Root Zone*
Spatial Coverage	*1000 to 25000 km2*
Quantization	*3–4 levels, ranging from dry to very wet*
Accuracy	*Moderate, ~75%*
Product delivery	*Upon request to within 3–4 days of request*

Table 1*: Standardized soil moisture product requirements for watershed scale applications.*

Model Calibration

Model calibration (**figure 2**) involves identifying model parameters which induce model behavior which is most closely related to observed system behavior thus providing for maximally accurate predictions of past behavior which, in theory, will correspond to maximally accurate future predictions.

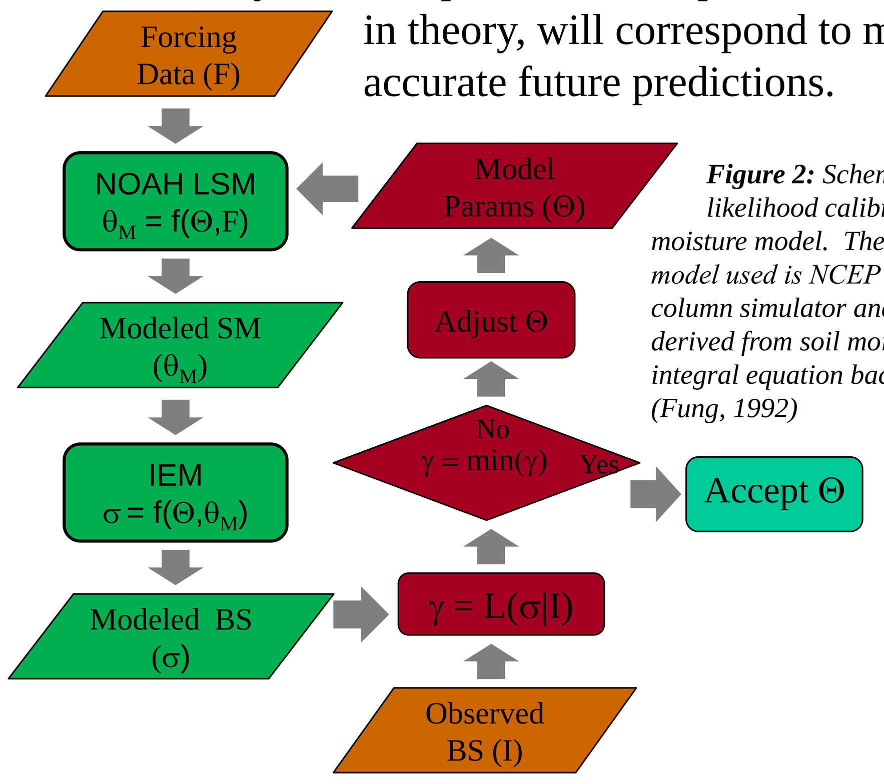

Figure 2: *Schematic for likelihood calibration of a soil moisture model. The land surface model used is NCEP's NOAH soil column simulator and backscatter is derived from soil moisture via the integral equation backscatter model (Fung, 1992)*

Study Site and Simulation Period

Walnut Gulch Experimental Watershed Kendall Station

- USDA operated
- Semi-arid, light vegetation, sandy soils
- Meteorological flux station provides 9 years recorded data at 20 minute intervals
- Time Domain Reflectometry (TDR) soil moisture probes provide 4 years of recorded data at 20 minute intervals

Figure 3*: Kendall Vegetation, 2005*

Simulation Period

- Mar. 9 – Sep. 6, 2004
- 81 day warm-up period
- Performance statistics collected May30 – Sep. 6 during the fall monsoon season.

Imagery

Date	Time	Instrument	Pixel Dimension	Incidence Angle	Wavelength	Polarization
June 9	10:16	ENVISAT	12.5 m	41.08^o	5.6 cm	VV
July 14	10:16	ENVISAT	12.5 m	41.08^o	5.6 cm	VV
Aug 2	10:16	ENVISAT	12.5 m	37.39^o	5.6 cm	VV
Aug 7		RADARSAT	12.5 m	35.93^o	5.6 cm	HH
Aug 17		RADARSAT	12.5 m	46.48^o	5.6 cm	HH

Table 2: *Summary of radar imagery available for this study. All imagery was obtained with 3 looks in 2004.*

Surface Roughness Characterization

Surface roughness characteristics of the imaged land surface was needed in order to extract moisture information. This was obtained using the method of Rahman et al., 2008 which uses multiple radar images at different viewing angles to differentiate the effects of roughness and dielectric constant information. This method requires knowledge of desiccated state soil moisture content for the area as well as an image of the environment at a dry point.

Likelihood Objective Function

Goodman's Speckle Model:

I is the observed backscatter intensity at a given location and time, σ is the mean intensity over a homogeneous target, and n is the speckle effect.

$$P(I \mid \sigma) = \frac{1}{\sigma} \times \exp\left(\frac{-I}{\sigma}\right)$$

$$I = \sigma \times n$$

$$P(n) = \exp(-n)$$

Since the mean speckle effect is zero σ will be the theoretical non-speckled backscatter value for the target.

Likelihood Estimator for σ Time Series:

Let $\boldsymbol{I} = \{I_j \mid \forall j\}$ where $\{j\}$ are image pixels of a homogenous target and $\boldsymbol{\Sigma} = \{\sigma_t \mid \forall t\}$ where $\{t\}$ are image times

$$P(I_t \mid \sigma_t) = 1/\sigma_t \times \exp(-I_t/\sigma_t)$$

$$L(\boldsymbol{\Sigma} \mid \boldsymbol{I}) \propto \prod_{t,j} (1/\sigma_t) \times \exp(-I_{j,t}/\sigma_t)$$

Acknowledgements

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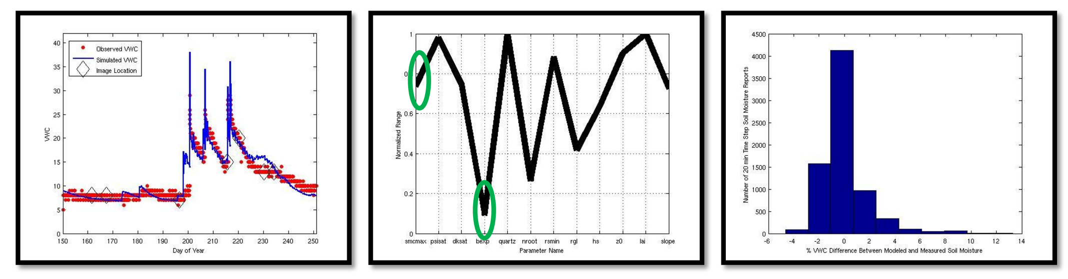
Results

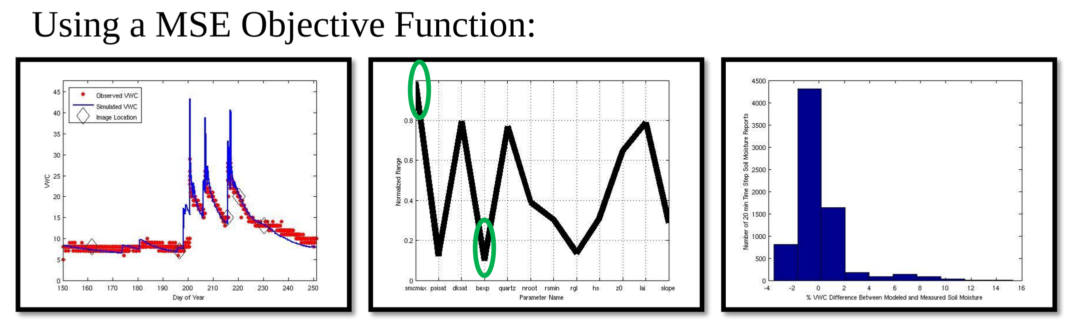
NOAH Calibration Using Soil Moisture Data

Calibration to ***TDR Measurements at Every Time Step***
Using a MSE Objective Function:



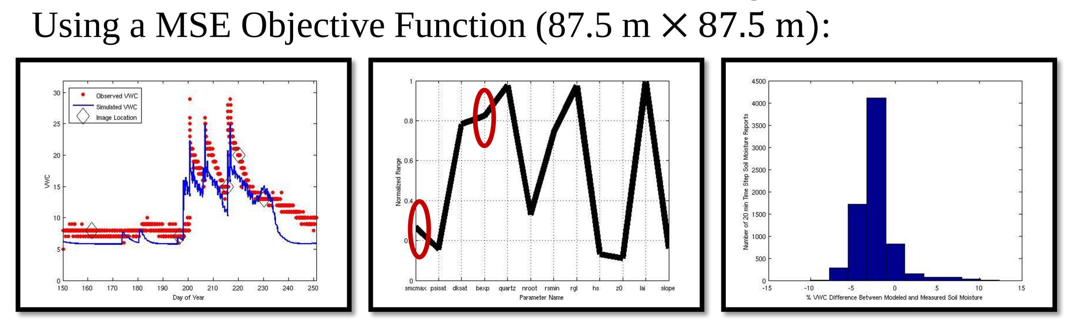
Time Series Comparison To TDR Measurements | Chosen Parameter Location In a Normalized Range | Histogram of Residuals at Every Time Step

Calibration to ***TDR Measurements at Image Times***
Using a MSE Objective Function:



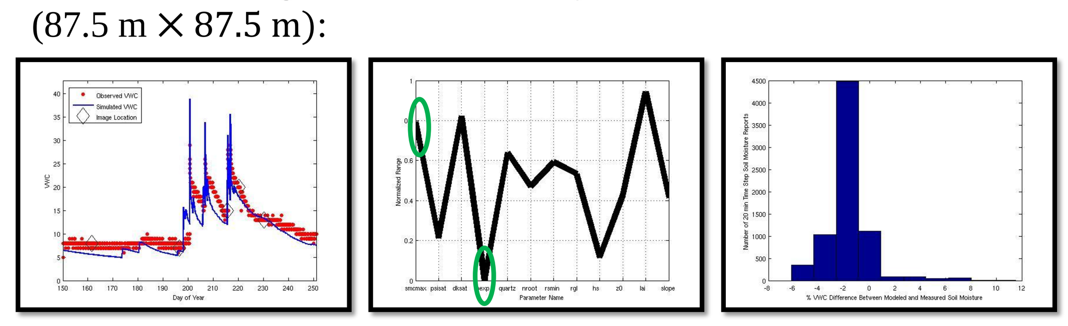
Time Series Comparison To TDR Measurements | Chosen Parameter Location In a Normalized Range | Histogram of Residuals at Every Time Step

Calibration to ***Soil Moisture Derived From Images***
Using a MSE Objective Function (87.5 m × 87.5 m):



Time Series Comparison To TDR Measurements | Chosen Parameter Location In a Normalized Range | Histogram of Residuals at Every Time Step

Calibration Using the ***Likelihood Objective Function***
(87.5 m × 87.5 m):



Time Series Comparison To TDR Measurements | Chosen Parameter Location In a Normalized Range | Histogram of Residuals at Every Time Step

Area (m)	Calibration Method	MSE All Times	MSE Images Times	Bias	95% Confidence VWC Difference
	TDR All	2.982	2.504	-0.043	3.125
	TDR at Image Times	3.825		-0.076	3.584
62.5	Likelihood	255.549	325.343	119.444	24.734
62.5	MSE	404.783	515.737	159.522	29.176
87.5	Likelihood	5.853	3.752	-14.790	4.780
87.5	MSE	9.728	6.885	-19.409	5.678
112.5	Likelihood	8.583	5.592	-17.909	6.565
112.5	MSE	7.545	5.499	-17.405	5.499

Table 3*: Calibration result statistics as compared to TDR measurements assuming different sized (square) homogenous areas.*

Conclusion

At small scales likelihood calibration comparing modeled and measured backscatter across multiple images reduces the effect of speckle noise on the objective function space as compared to assimilating image-derived soil moisture directly. This allows an automatic search algorithm to find the 'correct' minimizing region in the parameter space by reducing the gravity of local minimum caused by noisy observations. However, there is a point at which the homogeneity assumption fails when larger areas are considered and both types of parameter estimation procedures produce inferior results when compared to point-based TDR data.

In addition, while accuracy and precision requirements for soil moisture estimation can be met using a model calibration approach this approach suffers when using satellite imagery as calibration data due to the fact that satellite overpasses cannot capture the range of behaviors of the hydrologic system and thus do not contain information about all hydrologic processes. For example, in this demonstration peak soil moisture values are often grossly overestimated because no imagery in our collection captures surface behavior directly after or during a rainfall event.